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CO_2 Emissions and Economic Activity: a Short-to-Medium Run Perspective

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Abstract

This paper looks at the short-to-medium run impact of economic activity on CO_2 emissions in the United States, shifting the existing focus away from the long-run Environmental Kuznets Curve (EKC). Our novel methodological approach combines discrete wavelet transforms with dynamic factor models. This allows us to (i) estimate economic and emissions cycles at different frequencies, and (ii) let economic activity be estimated from many different economic variables, rather than focussing on a small number as in existing studies. From our results, one might at first conclude that emissions are not linked to economic activity in the short-run. However, when looking at the cycles uncovered at timescales of length one to three years, we see that there are indeed strong linkages. Policymakers therefore cannot be exclusively long-termist when evaluating the impact of economic policy on the environment.

JEL Classification: Q53, Q43, C01, C32, C38
Keywords: CO_2 Emissions, Environmental degradation, Factor Model, Wavelets, Cycles, Short-to-Medium Run

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1 Introduction

Are emissions only related to economic activity in the long run, or does interaction also take place in the the short-to-medium run? There has been extensive research into the existence of a long run relationship between emissions and economic variables and its shape; the so-called "Environmental Kuznets Curve" (EKC). The exclusive focus of the literature on the long run rather than the short-to-medium run, however, may not be entirely justified. With economic and environmental policy becoming more balanced in their importance to politicians and policymakers, it makes sense to study the emissions-economy linkage in phases shorter than electoral cycles. This is particularly relevant in the United States where topics like climate change can have a notable presence in presidential campaigns. Furthermore, the global rise in policy instruments such as emissions trading schemes use economic incentives to control emissions over short time spans. In the U.S. this has been seen through policies such as the Regional Greenhouse Gas Initiative. This paper therefore shifts the focus away from the EKC-type literature to re-focus attention on the short-to-medium run interplay between the economy and the environment.

In order to tackle this issue, we propose a novel methodological approach which combines the use of dynamic factor models with maximum overlap discrete wavelet transforms (MODWT) in analysing the growth rates of CO_2 emissions and a large dataset of economic variables. The MODWT allows us to decompose a time series into several 'timescales' which represent changes taking place over different cycle frequencies ranging from low to high, in other words in shorter phases than the 'long run'. Discrete wavelet transforms and related timescale decompositions have only recently been adopted in financial economics by studies looking at asset returns and macroeconomic variables and uncertainty, for example Ortu et al. (2013), Gencay and Signori (2015) and Xyngis (2017).

Dynamic factor models, on the other hand, have become widely used in modelling large macroeconomic datasets (recent examples include McCracken and Ng, 2016; Antolin Diaz et al., 2017; Fosten and Gutknecht, 2019; see Stock and Watson, 2016, for a survey). This approach estimates the factors which are common to a large number of series and can be implemented using Principal Components Analysis as suggested by Stock and Watson (2002a,b), Bai and Ng (2002) and Bai (2003). To the best of our knowledge, neither of these methodologies alone has been applied to the issue of the emissions-environment nexus, and the combination of the two methods is something which is of separate interest in itself. Our approach brings about several improvements in this literature.

The first main advantage of our approach is that the use of the “big data” factor model methodology allows us to analyse how a large number of different proxies for economic activity affect the environment. This is a substantial improvement over existing EKC studies which use standard regression techniques relying on the choice of a small selection of economic indicators.[1] The benefit of our paper is that we can first estimate the latent economic drivers which underpin several series like production, employment, consumer sentiment and so on, and see how these relate to emissions. The majority of previous studies only use a single series related to output such as GDP, see Al-Mulali et al. (2015) for an extensive survey. Other proxies have also been considered for economic activity: fuel prices (Balaguer and Cantavella, 2016), foreign direct investment (Lau et al., 2014), trade (Jebli et al., 2016) and transport (Pablo-Romero et al., 2017). The only paper to address this multiplicity of predictors is Auffhammer and Steinhauser (2012) who use data-snooping methods to select from a massive universe of different EKC specifications. The approach we take in our study will remove any reliance of the results on the choice of a particular variable to proxy economic activity.

The second advantage of our study is the use of the MODWT. In conjunction with the use of monthly data on the growth rates of CO_2 emissions and macroeconomic variables, this allows us to uncover short-to-medium run relationships.[2] We can therefore assess whether there are cycles in CO_2 emissions over frequencies ranging from one month to several years, and whether these link to economic cycles. This contrasts to a large proportion of existing EKC-type studies dating all the way back to the seminal works of Selden and Song (1994), Grossman and Krueger (1995) and Holtz-Eakin and Selden (1995), which use annual data on emissions across different countries. While these studies are important from the perspective of how economic development affects the

[1]This is particularly relevant in the case of time series studies using cointegration techniques, as these methods usually require the number of variables in the cointegrating vector to be small.

[2]The reason we focus on CO_2 in this paper is because its availability at the monthly frequency allows us to answer the research question regarding short-to-medium frequency cycles. For example, data on SO_2 emissions are only available at an annual level from the U.S. Energy Information Administration. This would not yield a sufficient sample to perform our analysis, nor would it allow us to make conclusions about the linkages between emissions and economic activity at frequencies as high as one month.

environment, they are not able to uncover short-to-medium run features in this relationship.[3]

In our preliminary results, we present the estimates of economic and emissions cycles over different timescales. We check the external validity of our methodology by examining the correlation between our decompositions of economic activity with widely-used business cycle-type measures for the U.S. Our measures display high correlation with several indices such as the Federal Reserve Economic Data (FRED) Leading Index, when the timescale is greater than one or two years. Since there are no widely-used indices of emissions cycles to the best of our knowledge, our timescale decompositions of CO_2 emissions are of standalone interest.

Our main results look at the relationship between the economic and emissions cycle variables and uncover several important findings. For total CO_2 emissions derived from energy consumption,[4] a simple baseline specification detects no short-run linkage between emissions and economic activity at the highest frequency of one month. This is because any short-to-medium term trends are masked at the noisy monthly frequency; a sentiment discussed in Bandi et al. (2019). On this evidence alone, we might be tempted to conclude that emissions are not linked to economic activity over short phases. However, when we increase the timescales to medium-run cycles of around one to three years, we find that a relationship indeed does exist. This indicates that the trends which are uncovered by filtering at a lower frequency than one month do show a significant impact of economic conditions on emissions, and so the conclusions change when using an appropriate timescale decomposition. We also find that very similar results hold for three disaggregated components of energy CO_2 emissions, namely: coal, natural gas and petroleum. However, when looking at further disaggregation, we find that many small components such as CO_2 emissions from kerosene consumption are not linked to economic activity in any significant way at any timescale.

We conduct a variety of detailed additional checks to determine the robustness of our results. Firstly, we check for polynomial nonlinearity in our baseline specification, motivated by (but not derived from) the idea of the EKC in levels. The use of nonlinear functions of the principal components has been explored in predicting macroeconomic variables by Bai and Ng (2008, 2009) However, our main findings do not alter qualitatively when adding in these additional nonlinear

[3] A small number of EKC-type studies have used monthly time series, such as Burnett et al. (2013). Even higher frequency CO_2 data have been observed in very localised areas in studies such as Hood et al. (1999).

[4] As discussed in the Data section, while some studies have identified issues with using emissions derived from energy consumption, such as simultaneity bias in regressions involving energy variables on the right-hand side, in our study we do not have this issue and are justified in using these series which are available at the monthly frequency.

terms. We also find our results to be relatively robust to changes in sample split, and to the choice of wavelet filter used in performing the MODWT.

The remainder of this paper is organized as follows. Section 2 introduces the new methodology. Section 3 describes the data source, and gives details and charts of the variables used. Section 4 provides the results of the baseline version of the methodology. Section 5 runs sets of additional robustness checks. Finally, Section 6 concludes the paper.

2 Methodology

We wish to explore the short-to-medium run dynamics between emissions, E_t, and an $N \times 1$ vector of economic variables, $\mathbf{X}_t$, both of which are taken to be non-stationary unit root processes in levels. For the growth rates of these variables, we define the lower case $e_t = \ln(E_t) - \ln(E_{t-1})$ to be emissions growth, and $\mathbf{x}_t = \ln(\mathbf{X}_t) - \ln(\mathbf{X}_{t-1})$ as the growth of the economic series.[5] We have a total of T monthly observations on the variables e_t and $\mathbf{x}_t$.

We assume that the economic variables exhibit a factor structure as in Stock and Watson (2002a,b), and can be well-explained by a low-dimensional set of r common factors, $\mathbf{f}_t$, as follows:

$$\mathbf{x}_t = \mathbf{\Lambda}\mathbf{f}_t + \mathbf{u}_t \tag{1}$$

for $t = 1, ..., T$, where $\mathbf{\Lambda}$ is an $N \times r$ matrix of factor loadings and $\mathbf{u}_t$ is an $N \times 1$ vector of idiosyncratic disturbances. In principle, the number of economic predictors, N, is allowed to be large relative to the sample size. Since both $\mathbf{\Lambda}$ and $\mathbf{f}_t$ are unknown, Stock and Watson (2002a,b) suggest to estimate them by Principal Components Analysis (PCA) by minimising the sum of squared residuals in Equation (1). The factor estimates, denoted $\widehat{\mathbf{f}}_t$, are extracted by setting the $T \times r$ matrix $\widehat{\mathbf{f}}$ as the r eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix $\mathbf{x}\mathbf{x}'/NT$, where $\mathbf{x}$ is the $T \times N$ matrix collecting all observations $\mathbf{x}_t$.[6]

Having estimated the economic factors, the emissions-economy relationship is explored through-

[5] A full description of the economic series we consider is given in the Data section.
[6] The variables in $\mathbf{x}_t$ are standardised to have mean 0 and variance 1.

out this paper based on the short-run regression model:

$$e_t = \alpha + \beta' \widehat{\mathbf{f}}_t + v_t \tag{2}$$

for $t = 1, ..., T$. This is known as the "factor-augmented model" as in Stock and Watson (2002a,b) and Bai and Ng (2006), in the sense that the factors are first estimated and then plugged in to a second-stage model with emissions, e_t, as the dependent variable. We start out with this simple specification, but we will expand the set of regressors included Equation (2) in subsequent robustness checks. To the best of our knowledge this is the first paper to use factor-augmented approaches in modelling emissions. The intuition is that the factors capture the bulk of co-movements in the economy, which are used to explain CO_2 emissions; something which reduces the reliance of existing studies on the selection of particular economic variables to capture the emissions-economy relationship.

While Equation (2) gives the short-run relationship bewteen emissions and the economy, the primary interest of this paper is to determine the nature of this relationship as we move towards the medium-run by decomposing the series to different timescale components. The aim is to have a multiresolution analysis (MRA) of the $T \times 1$ time series $\mathbf{e}$ and the $T \times r$ matrix $\widehat{\mathbf{f}}$, which decomposes the original monthly series into J different time scales plus a 'smooth' term. The intuition behind this decomposition is that the first J series represent the changes in the original time series taking place over lower and lower frequencies, and the smooth term picks up the long term movement. This is done in such a way that the $J + 1$ components sum up to the original time series as follows:

$$\mathbf{e} = \sum_{j=1}^{J} \mathbf{e}^{(j)} + \mathbf{S}_e^{(J)} \tag{3}$$

and

$$\widehat{\mathbf{f}} = \sum_{j=1}^{J} \widehat{\mathbf{f}}^{(j)} + \mathbf{S}_{\widehat{f}}^{(J)} \tag{4}$$

where the terms $\mathbf{e}^{(j)}$ and $\widehat{\mathbf{f}}^{(j)}$ are known as the jth level details for $j = 1, ..., J$ whereas $\mathbf{S}_e^{(J)}$ and $\mathbf{S}_{\widehat{f}}^{(J)}$ are the Jth level smooths. At this stage we would additionally note that MRA of factors which have been estimated along the lines of Stock and Watson (2002a,b) is something which we have not seen in the literature and therefore is of separate econometric interest to applied researchers.[7]

Each of the components of the MRA is obtained using the MODWT. For a very detailed description of this procedure, the reader is referred to Percival and Walden (2000) and Gencay and Signori (2015) but we provide a brief description here. The MODWT of $\mathbf{e}$ is a set of $J+1$ time series $[\mathbf{W}_e^{(1)}, ..., \mathbf{W}_e^{(J)}, \mathbf{V}_e^{(J)}]$. The time series $\mathbf{W}_e^{(j)}$ gives the MODWT wavelet coefficients for changes which take place on a scale 2^{j-1} (so with monthly data, for $j = 3$, this denotes changes which take place over $2^2 = 4$ months and so on). $\mathbf{V}_e^{(J)}$ contains the MODWT scaling coefficients for changes taking place on a scale J. These are respectively calculated from the original series as $\mathbf{W}_e^{(j)} = \mathcal{W}_e^{(j)}\mathbf{e}$ and $\mathbf{V}_e^{(J)} = \mathcal{V}_e^{(J)}\mathbf{e}$ where $\mathcal{W}_e^{(j)}$ and $\mathcal{V}_e^{(J)}$ are $T \times T$ matrices. The calculation of the MODWT wavelet and scaling coefficients require us to specify wavelet and scaling filters, which are in turn used to calculate $\mathbf{W}_e^{(j)}$, $\mathbf{V}_e^{(J)}$, $\mathcal{W}_e^{(j)}$ and $\mathcal{V}_e^{(J)}$ by filtering the original series, $\mathbf{e}$. The simplest and most commonly applied filter is the Haar filter, though the Daubechies family of filters is also often used. Our analysis will mostly be based on the Haar filter but we will check the robustness of our results to this choice.

To complete the description, the components of the MRA from Equations (3) and (4) can be computed from the MODWT. The jth level detail for $\mathbf{e}$ is defined as $\mathbf{e}^{(j)} = \mathcal{W}^{(j)\prime}\mathbf{W}_e^{(j)}$ where $\mathbf{W}_e^{(j)}$ and the Jth level smooth is $\mathbf{S}_e^{(J)} = \mathcal{V}^{(J)\prime}\mathbf{V}_e^{(J)}$.

Using this, we can now describe the finalized timescale-specific baseline regression model which will form the foundation of the analysis in the remainder of this paper. Based on the factor-augmented model in Equation (2), we make the following adjustment to relate emissions to the the economy at each separate timescale:

$$e_t^{(j)} = \alpha^{(j)} + \beta^{(j)\prime}\widehat{\mathbf{f}}_t^{(j)} + v_t^{(j)} \quad \text{for } j = 1, ..., J \tag{5}$$

The intuition behind using this equation is that it may help us to uncover relationships which exist between emissions and the economy at different timescales, which may not be present when analysing the relationship between the original monthly growth rate series. In the field of financial economics, several recent papers such as Ortu et al. (2013), Xyngis (2017), Kang et al. (2017)

[7] The paper by Rua (2011) does look at applying wavelet decompositions to factor models, but their approach first decomposes the original $\mathbf{x}_t$ series before estimating the factors. We do not use this approach here as the statistical properties of such a procedure have not yet been researched. On the other hand, the statistical properties of $\widehat{\mathbf{f}}_t$ are already well known and so the MRA can be directly applied.

and Bandi et al. (2019) have established that asset returns relate to macroeconomic variables and uncertainty only at lower frequencies and not at high frequencies.

3 Data

The carbon emissions data we use are taken from the U.S. Energy Information Administration (EIA) Monthly Energy Review, which contains monthly carbon dioxide emissions from energy consumption.[8] We consider different possible dependent variables for the emissions variable $e_t^{(j)}$ in Equation (5). These series, listed in Table 1, contain monthly observations from January 1973 to December 2018 and include the CO_2 emissions by source, broken down by the consumption of coal, natural gas and petroleum. The emissions from consumption of petroleum are further broken down into 10 subcomponents. CO_2 emissions derived from energy consumption are used by many previous empirical studies (see Soytas et al., 2007, Soytas and Sari, 2009 and Halicioglu, 2009 for some recent examples). These data are particularly useful in the current paper as they are available at the monthly level which allows us to look at the short-to-medium run behaviour of emissions. One potential drawback of using emissions from energy consumption, noted by Burnett et al. (2013), is if the principal interest is in determining the relationship between emissions and energy use, which can suffer from simultaneity issues. This is not the purpose of our paper, and so these series are appropriate for our analysis.

Figure 1 displays the time series for total energy CO_2 emissions (CO2-TOT) over the full sample period. Total emissions in levels are non-stationary as discussed in the literature and will be used in growth rates by log-differencing for the analysis as mentioned in the previous section.[9] While there is generally an upwards trend in total energy CO_2 emissions throughout the 1980s and 1990s, from the end of the 2000s emissions begin to decline. This can be explained by plotting the individual components, where Figure 2 below reveals that petroleum-based emissions (CO2-PET) account for the largest proportion of the total energy CO_2 emissions and Figure 5 displayed in the Appendix shows that these emissions experienced a sharp drop in the late 2000s. This has become known as the "U.S. Petroleum Consumption Surprise" and has various explanations, mostly attributed to a

[8]Available at: https://www.eia.gov/totalenergy/data/monthly/ [Last accessed: 03/04/19].

[9]The non-stationarity of emissions was confirmed by running tests including the standard Augmented Dickey-Fuller unit root test and the Zivot and Andrews (1992) test which allows for a structural break. The test results are not presented here and are available from the author on request.

Table 1: CO_2 Emissions and Economic Variable Descriptions and Short Codes

Code	CO_2 Emissions from Energy Consumption
CO2-COAL	Coal, Including Coal Coke Net Imports
CO2-GAS	Natural Gas, Excluding Supplemental Gaseous Fuels
CO2-AVI	Aviation Gasoline
CO2-DIST	Distillate Fuel Oil, Excluding Biodiesel
CO2-HCL	Hydrocarbon Gas Liquids
CO2-JET	Jet Fuel
CO2-KER	Kerosene
CO2-LUB	Lubricants
CO2-MOT	Motor Gasoline, Excluding Ethanol
CO2-PETC	Petroleum Coke
CO2-RES	Residual Fuel Oil
CO2-OTH	Other Petroleum Products
CO2-PET	Petroleum, Excluding Biofuels
CO2-TOT	Total Energy CO_2 Emissions

Code	Economic Variables
IP	Industrial Production Index (INDPRO)
RS	Capacity Utilization: Manufacturing (CUMFNS)
AUTO	Motor Vehicle Retail Sales (DAUTOSAAR)
UNEM	Civilian Unemployment Rate (UNRATE)
BP	Building Permits (PERMIT)
HS	Housing Starts (HOUST)
EMP	Employment (PAYEMS)
CSI	Uni. Michigan: Consumer Sentiment (UMCSENT)
PPI	Producer Price Index (WPSFD49207)
CPI	Consumer Price Index (CPALTT01USM661S)

Notes: The codes in parentheses for the economic variables are the FRED Economic Data identifier codes.

drop in vehicle miles travelled in the transportation sector.[10] Emissions due to coal consumption have fallen to below their 1980s level.

The emissions series displayed here have been seasonally adjusted using the X-13 ARIMA adjustment of the U.S Census Bureau.[11] It is important to note that, although the wavelet methodology we employ is capable of filtering out seasonal patterns, we must seasonally adjust CO_2 emissions first because many of the economic variables we consider are not available in non-seasonally adjusted form. We therefore avoid looking for relationships between variables with differing seasonal patterns.

[10]For example, see the report “Explaining the U.S. Petroleum Consumption Surprise” by the Executive Office of the President. https://www.weforum.org/agenda/2015/07/the-surprising-decline-in-us-petroleum-consumption/ [Last accessed: 13/01/17]

[11]This is performed in the statistical computing software R, as are all of the main results in this paper.

Figure 1: Total CO_2 Emissions 1978-2018 (seasonally adjusted using X13-ARIMA)

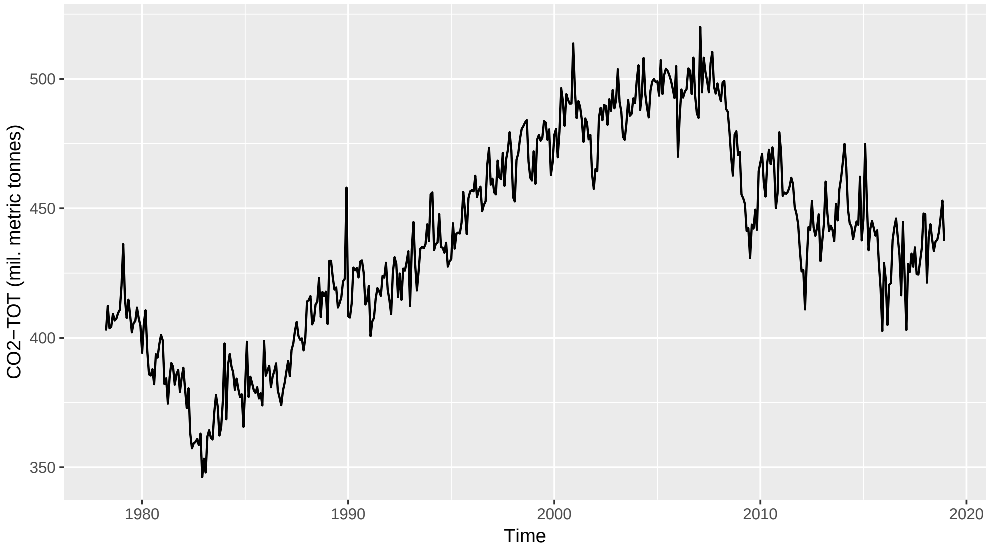
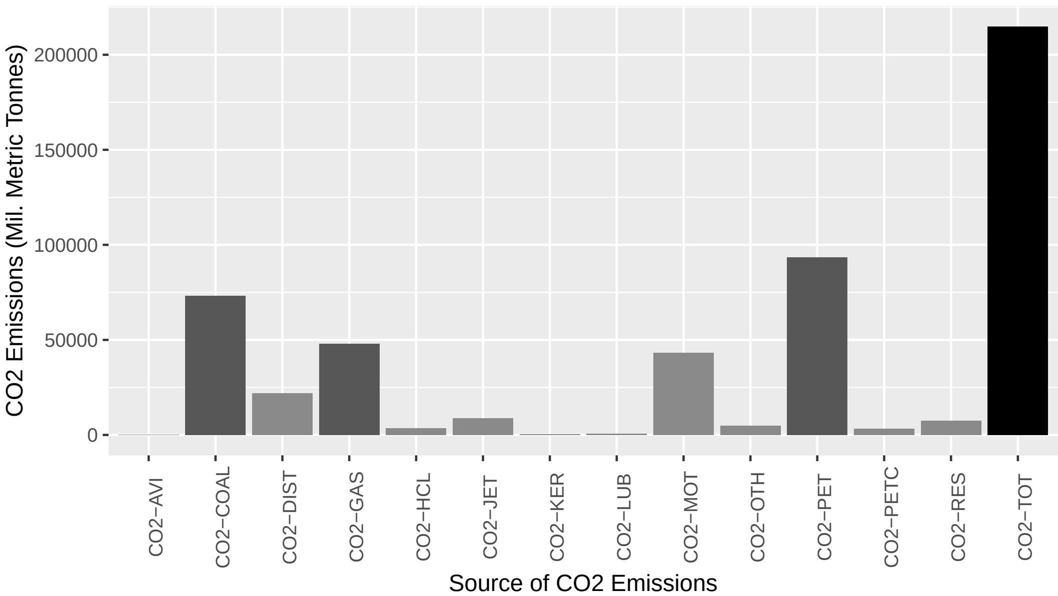


Figure 2: CO_2 Emissions by Source, Total from 1978-2018



Notes: The height of the bars represents the sum of (seasonally-adjusted) emissions of each component over monthly time periods from April 1978 to December 2018. Note that CO2-TOT (black) is the sum of CO2-COAL, CO2-GAS and CO2-PET (dark grey), whereas CO2-PET is the sum of all other components (lighter grey).

The set of $N = 10$ economic variables we use are chosen to match existing studies which employ small-scale factor models, such as Banbura et al. (2013), Bańbura and Modugno (2014) and Antolin Diaz et al. (2017). These variables are also listed in Table 1, and are mostly real series related to production, construction, employment and consumer sentiment. All data are readily available from the St. Louis Federal Reserve Economic Data (FRED).[12] While we do not envisage a "story" linking each of these variables separately with emissions, we include these variables as they are often used to estimate the factors underpinning economic activity. These data are also at the monthly frequency, and the common data span of all of the variables is from April 1978 to December 2018. We therefore use this sample of $T = 489$ observations as the common sample with CO_2 emissions in all of our analysis. As with emissions, since all of these variables are $I(1)$ unit root processes, we transform them to stationarity by log-differencing to give the monthly growth rate.

While our factor-based methods are capable of dealing with much larger datasets than this, for example the Stock and Watson dataset which contains over a hundred series, studies such as Antolin Diaz et al. (2017) find that the series in Table 1 pick up the bulk of movements in the real economy with only a single factor. We therefore do not explore adding in the remaining Stock and Watson variables and set $r = 1$ in this small-scale dataset.

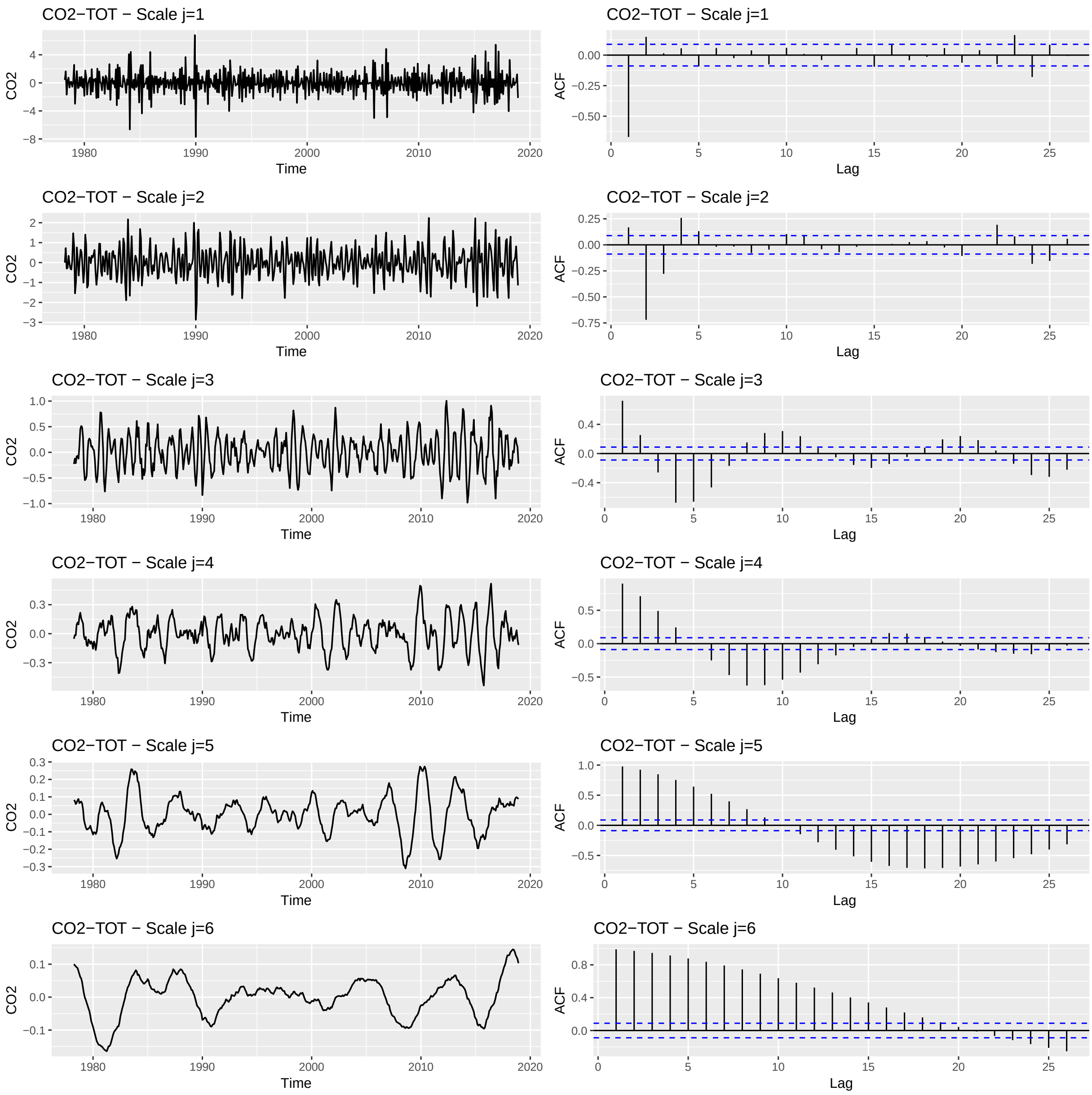
4 Results

We first derive the MRA decompositions from Equations (3) and (4) for the CO_2 emissions series and the single estimated factor. The decompositions are taken for a maximum of $J = 6$ scales, which corresponds to changes which occur over a period of 32 months; in other words just under 3 years. Figures 3 and 4 display the MRA for total energy CO_2 emissions and the factor respectively (the MRA for the coal, gas and petroleum series and further disaggregates can be found in an Online Appendix). These decompositions are based on the MODWT using the Haar filter.

From these figures it is clear that movements in both emissions and economic factors are somewhat noisy when looking at the shortest timescale, $j = 1$. It is only when we look at scales from around $j = 4$, which depict changes over timescales of 8 months or more, do we start to observe cyclical behaviour in the two series. This can be seen in the decomposition of the economic factor in Figure 4, where the economic crisis of 2007-08 becomes more visually apparent at the lower frequencies. As a further note, since the wavelet decomposition is linked to cumulation of the higher-frequency growth rates, it is evident that there is therefore much higher persistence in the

[12] Available at: https://fred.stlouisfed.org/ [Last accessed: 29/03/19].

Figure 3: MRA for Total Energy CO_2 Emissions, with Autocorrelation Plots

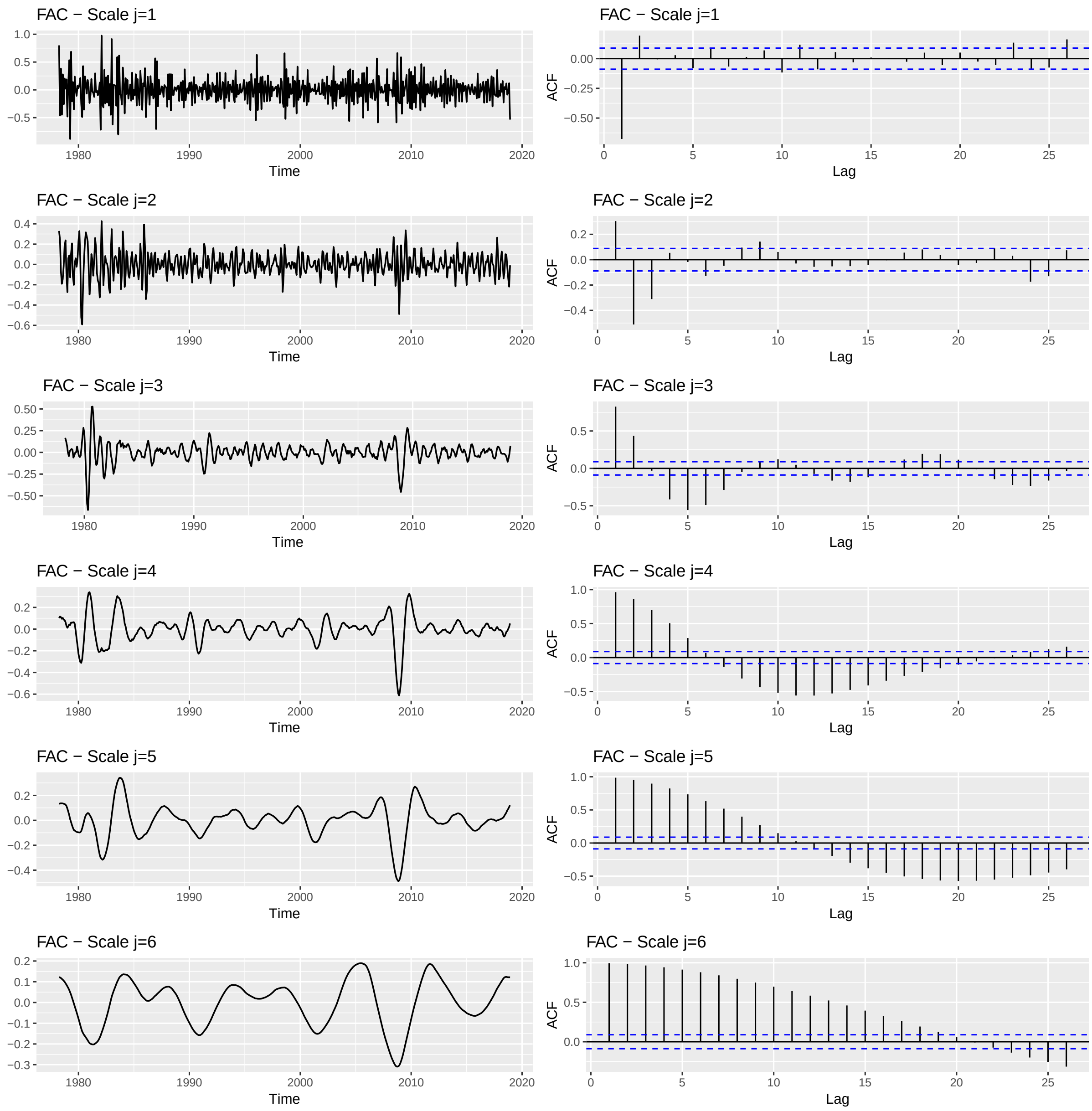


Notes: The MRA is based on the MODWT using the Haar wavelet filter.

series toward the $j = 6$ scale, as can be seen from the autocorrelation plots. However, in spite of the increased persistence the resulting series are still stationary.

It is difficult to provide a measure of external validity for the constructed series for CO_2 emissions in Figure 3 as we are not aware of any similar indices which aim to measure emissions cycles. However, there are several widely-used economic activity indices for the U.S. which we could use to

Figure 4: MRA for the Single Factor, with Autocorrelation Plots



Notes: The MRA is based on the MODWT using the Haar wavelet filter.

compare with the different timescale decompositions in Figure 4. Table 2 shows the correlation of each of the timescales of the estimated factor displayed in Figure 4 with four different economic activity indicators. These activity indicators are: the FRED Leading Index, the Philadelphia (Philly) Federal Reserve General Activity Index, and two versions of the Chicago Fed National Activity Index (NAI).

Table 2: Correlation of Estimated Factor at Different Timescales with Economic Activity Indices

	Factor Estimate by Scale (j)					
	$\widehat{\mathbf{f}}^{(1)}$	$\widehat{\mathbf{f}}^{(2)}$	$\widehat{\mathbf{f}}^{(3)}$	$\widehat{\mathbf{f}}^{(4)}$	$\widehat{\mathbf{f}}^{(5)}$	$\widehat{\mathbf{f}}^{(6)}$
FRED Leading Index	0.048	0.104	0.328	0.532	0.673	0.732
Philly Fed General Activity Index	0.040	0.084	0.354	0.522	0.645	0.577
Chicago Fed National Activity Index	0.445	0.396	0.500	0.632	0.700	0.618
Chicago Fed National Activity Index MA3	0.091	0.129	0.437	0.672	0.787	0.705

The results in Table 2 show that at a frequency from $j = 1$ (one month) to $j = 3$ (four months), the decomposed factor estimate has a low correlation with these measures of business cycle economic activity, with the exception of the original version of the Chicago Fed NAI. This is perhaps to be expected as the Chicago Fed themselves note that the original NAI is a noisy measure of cycles and that their MA3 version, which takes a 3-period moving average of the NAI, "tracks economic expansions and contractions" better than the original index.[13] We see that the highest correlation of the factors with the different economic activity indices occurs at either $j = 5$ or $j = 6$, which corresponds to timescale decompositions with frequencies between two and three years.

To assess the relationship between cycles of economic activity and emissions, Table 3 displays the results of the baseline linear regression model specified in Equation (5) across timescales $j = 1, ..., 6$ for total energy emissions and its three main components (coal, gas and petroleum). This version of the equation does not include any additional regressors, which will be included later on in the paper. The regression results for the smaller subcomponents of CO_2 emissions from petroleum can be found in the Online Appendix.

The results for total energy CO_2 emissions, at the bottom of Table 3, reveal some rather interesting findings. For the first three scales, $j = 1, ..., 3$, we see no evidence of a meaningful relationship between emissions and the factor, with R^2 lower than 2% in each case. This indicates that the noise inherent of these series at the first timescales induces the conclusion that short-run economic and emissions cycles are not linked in a significant way. A similarly low R^2 has also been detected at the first timescales in the finance studies cited above (Xyngis, 2017; Bandi et al., 2019).

However, the R^2 is far larger when the series are decomposed to the lower frequencies $j = 4, 5, 6$ denoting cycles of length between one and three years. Predictive power peaks at $j = 5$ where more

[13]See the Background Information to the NAI: https://www.chicagofed.org/∼/media/publications/cfnai/background/cfnai-background-pdf.pdf [Last accessed: 01/11/17]

Table 3: Regression Results by Timescale - Baseline Specification

		Scale					
		1	2	3	4	5	6
	$\beta^{(j)}$	0.300	0.242	0.572	1.216	1.017	0.582
CO2-COAL	t-Stat	[0.553]	[0.438]	[1.666]	[3.332]	[3.413]	[0.845]
	R^2	0.001	0.001	0.014	0.182	0.321	0.280
	$\beta^{(j)}$	-1.053	0.698	0.218	0.351	0.580	0.221
CO2-GAS	t-Stat	[-0.884]	[0.922]	[0.339]	[0.855]	[2.664]	[0.967]
	R^2	0.007	0.003	0.001	0.014	0.264	0.165
	$\beta^{(j)}$	0.117	-0.554	0.451	0.301	0.408	0.472
CO2-PET	t-Stat	[0.251]	[-1.580]	[1.328]	[1.121]	[3.367]	[2.365]
	R^2	0.000	0.011	0.029	0.065	0.362	0.439
	$\beta^{(j)}$	-0.134	-0.004	0.407	0.608	0.629	0.443
CO2-TOT	t-Stat	[-0.286]	[-0.010]	[1.130]	[2.966]	[5.998]	[1.537]
	R^2	0.000	0.000	0.016	0.179	0.525	0.690

Notes: This table presents the Ordinary Least Squares (OLS) estimate of the slope coefficient from Equation (5) for each timescale, along with corresponding t-statistic and coefficient of determination (R^2). The t-statistics are calculated using Newey-West HAC robust standard errors with a lag length truncation of $2^j - 1$.

than 50% of the variation in $e_t^{(5)}$ is explained by the factor $\widehat{\mathbf{f}}_t^{(5)}$, which is highly significant according to the t-statistic calculated using the Newey and West (1987) HAC robust standard errors. Overall this indicates that a meaningful relationship between CO_2 emissions can be uncovered when the one-to-three year medium-run trends are extracted using an appropriate timescale decomposition. This finding in the context of the emissions-economy relationship is related to the idea of Bandi et al. (2019) who state that *"hard-to-detect predictability over short horizons is generally viewed as the result of a low signal-to-noise problem... The aggregation [...] over longer horizons, however, operates as a signal extraction process uncovering predictability."* (p.120).

The results for the subcomponents of energy CO_2 emissions for coal, gas and petroleum yield similar insights to that of total CO_2 energy emissions. In all cases, predictive power of the estimated economic factor is at its highest for timescale $j = 5$ which neatly aligns with the finding for total CO_2 emissions, although the 4th-scale β coefficient has similar statistical significance to the 5th in the case of coal CO_2 emissions.

When digging down into the further disaggregated components, the table in the Online Appendix shows that, while this result is similar in some of the components, for emissions from kerosene, hydrocarbon gas liquids, motor gasoline, coke, residual fuel oil and other petroleum products, there is no statistically significant relationship with economic activity at any timescale. In the smaller noisy components like kerosene, it makes sense that economic variables do not predict emissions growth, whereas for motor gasoline emissions the story is perhaps more one of inelasticity of car travel with respect to economic conditions.[14]

5 Robustness Checks

5.1 Nonlinearity

The linearity of factor-augmented models has been relaxed in a number of papers, most notably Ludvigson and Ng (2007), Bai and Ng (2008) and Bai and Ng (2009). They suggest various approaches to incorporate nonlinearity which can potentially improve predictions of the target variable if we believe they are related in some way to the volatility of the predictors. In the context of emissions, it may be plausible to think that the volatility of economic activity is related to energy CO_2 emissions if regularly speeding up and slowing down industrial production (or other aggregate economic activity) is more energy intensive than a stable industrial production schedule.

The simplest specification considered in the aforementioned papers is to augment Equation (2) with further polynomial terms in the estimated factors. Here we extend the ideas of Bai and Ng (2008, 2009) to our scale-dependent context of Equation (5) by writing an expanded model as:

$$e_t^{(j)} = \alpha^{(j)} + \beta_1^{(j)\prime}\widehat{\mathbf{f}}_t^{(j)} + \beta_2^{(j)\prime}(\widehat{\mathbf{f}}_t^{(j)})^2 + \beta_3^{(j)\prime}(\widehat{\mathbf{f}}_t^{(j)})^3 + v_t^{(j)} \quad \text{for } j = 1, ..., J \tag{6}$$

While this looks like an Environmental Kuznets Curve, because we have directly specified this equation in the polynomials of factors estimated on growth rates, we do not make any claim that this is linked to the long-run Kuznets Curve in levels. Note that the assumption of a Kuznets curve in levels of emissions uses polynomials of $I(1)$ variables which may not themselves be $I(1)$. Here we simply take the stationary $I(0)$ emissions growth and estimated factor and form quadratic and cubic terms which are still stationary, thereby avoiding the issue of mixing the orders of integration.

Table 4 presents the regression results for the same series as in Table 3. We can see that

[14] The majority of past studies estimate U.S. price elasticties of automobile demand to be close to zero, see Dong et al. (2012) for a survey of several findings.

Table 4: Regression Results by Timescale - Nonlinear Specification

			Scale (j)					
			1	2	3	4	5	6
CO2-COAL	Linear	$\beta_1^{(j)}$	0.165	-0.488	0.403	1.076	1.048	0.918
		t-Stat	[0.189]	[-0.696]	[0.741]	[2.328]	[1.773]	[1.056]
	Square	$\beta_2^{(j)}$	0.898	0.844	-0.121	1.453	0.602	0.116
		t-Stat	[2.027]	[0.612]	[-0.239]	[0.874]	[0.366]	[0.066]
	Cubic	$\beta_3^{(j)}$	0.399	9.458	1.199	2.619	0.302	-9.420
		t-Stat	[0.230]	[2.155]	[0.638]	[0.841]	[0.065]	[-0.508]
		R^2	0.003	0.009	0.016	0.193	0.328	0.335
CO2-GAS	Linear	$\beta_1^{(j)}$	-1.835	-0.959	-0.324	0.724	0.632	0.276
		t-Stat	[-1.531]	[-1.073]	[-0.384]	[1.136]	[1.689]	[0.957]
	Square	$\beta_2^{(j)}$	0.837	2.362	1.454	-1.623	-0.013	-0.567
		t-Stat	[0.847]	[0.934]	[2.040]	[-1.433]	[-0.020]	[-0.351]
	Cubic	$\beta_3^{(j)}$	2.879	21.652	5.111	-4.749	-0.599	-2.619
		t-Stat	[0.735]	[3.026]	[1.729]	[-1.493]	[-0.208]	[-0.424]
		R^2	0.012	0.025	0.011	0.030	0.265	0.177
CO2-PET	Linear	$\beta_1^{(j)}$	-0.199	-0.779	0.243	0.504	0.355	0.555
		t-Stat	[-0.301]	[-1.808]	[0.662]	[1.594]	[1.917]	[2.238]
	Square	$\beta_2^{(j)}$	-0.459	-1.167	1.302	-0.085	0.266	-1.553
		t-Stat	[-1.079]	[-1.130]	[2.839]	[-0.131]	[0.964]	[-0.889]
	Cubic	$\beta_3^{(j)}$	1.267	2.377	2.468	-1.790	0.877	-5.219
		t-Stat	[1.056]	[0.922]	[2.139]	[-1.165]	[0.771]	[-0.594]
		R^2	0.003	0.018	0.057	0.093	0.369	0.489
CO2-TOT	Linear	$\beta_1^{(j)}$	-0.560	-0.690	0.086	0.686	0.608	0.593
		t-Stat	[-0.900]	[-1.366]	[0.204]	[2.377]	[3.215]	[1.783]
	Square	$\beta_2^{(j)}$	0.173	0.145	0.901	0.124	0.294	-0.817
		t-Stat	[0.408]	[0.135]	[2.278]	[0.173]	[0.650]	[-0.871]
	Cubic	$\beta_3^{(j)}$	1.605	8.648	3.052	-0.532	0.544	-5.819
		t-Stat	[1.145]	[2.512]	[2.144]	[-0.322]	[0.375]	[-0.889]
		R^2	0.004	0.015	0.033	0.184	0.529	0.737

Notes: This table presents the Ordinary Least Squares (OLS) estimate of the three slope coefficients from Equation (6) for each timescale, along with corresponding t-statistic and coefficient of determination (R^2). The t-statistics are calculated using Newey-West HAC robust standard errors with a lag length truncation of $2^j - 1$.

the results do not change significantly from the baseline specification. In all cases, the highest explanatory power in terms of R^2 comes at the larger timescales. The results for total energy CO_2 emissions (CO2-TOT) are quite robust to inclusion of the nonlinear terms, which are insignificant in almost all cases (except in some with very low R^2). This indicates that the baseline linear timescale specification of Equation (5) seems to be appropriate. The results for the coal, gas and petroleum components are also qualitatively similar to those of Table 3 where we can see that the non-linear terms are not significant.

5.2 Structural Breaks

In previous sections we alluded to the fact that structural change has taken place in the composition and trends of U.S. energy consumption and therefore so too in the CO_2 emissions from energy consumption. For example, the U.S. Petroleum Consumption Surprise in the 2000s caused an unexpected decline in total CO_2 emissions. There has also been a declining importance of coal over the last few decades although, as shown in Figure 6 in the Appendix, the proportional change relative to gas and petroleum was not large until the most recent periods. In light of these points, even though we work in stationary growth rates and not levels of emissions, there may still be reason to analyse the short-to-medium run behaviour of emissions over different historic sub-periods.

In the context of factor models for macroeconomic series, there has been a significant amount of research on structural breaks in the factor loadings. Papers such as Stock and Watson (2009) and Breitung and Eickmeier (2011) suggest that a large structural break occurred in the loadings in around 1984, corresponding to the date identified as the "Great Moderation". Since the majority of our sample is post-1984 this is unlikely to have affected the results in the earlier section. However, it makes sense to analyse sub-samples post-1984 for a structural break analysis. We therefore present results splitting the sample into two sections of 16 years: 1986-2002 and 2002-2018. This yields two sub-samples with $T = 192$ observations over which to check our results.[15]

Table 5 presents the results of the regression in Equation (5) over the two different subsamples. The results reveal that the relationship between total energy CO_2 emissions and the economic factor is qualitatively rather robust across the two subsamples. In both of the two sub-samples we see predictive power peaking after timescale $j = 5$, with little predictive power in small timescales. One small difference relative to the results in Table 3 is that the largest R^2 for CO2-TOT appears in scale $j = 6$ rather than $j = 5$ though this does not alter the overall message in the results. The findings in the other subcomponents also show some similar small differences (such as in CO2-PET where the R^2 also peaks at scale $j = 6$). Overall, the linkage between emissions and the economy

[15]We also conducted a more granular sub-sample analysis by splitting the data into 5 sections of 8 years: 1978-1986, 1986-1994, 1994-2002, 2002-2010 and 2010-2018. However, since this gave only $T = 96$ observations we felt this to be too low to present, and the instability seen in the results may have been due to the small sample size. The results are available upon request to those interested.

Table 5: Regression Results by Timescale - Subsamples 1986-2002 and 2002-2018

			Scale (j)					
			1	2	3	4	5	6
CO2-COAL	1986-2002	$\beta^{(j)}$	0.142	-0.124	0.782	0.969	1.016	0.611
		t-Stat	[0.468]	[-0.170]	[3.018]	[3.483]	[10.761]	[2.344]
		R^2	0.000	0.000	0.081	0.306	0.704	0.442
	2002-2018	$\beta^{(j)}$	-1.226	-0.501	0.306	1.413	0.948	0.287
		t-Stat	[-2.652]	[-0.838]	[0.621]	[4.767]	[4.567]	[1.994]
		R^2	0.035	0.004	0.005	0.534	0.684	0.667
CO2-GAS	1986-2002	$\beta^{(j)}$	-1.050	0.939	1.155	0.574	0.907	0.363
		t-Stat	[-0.784]	[0.841]	[2.069]	[1.251]	[4.556]	[0.962]
		R^2	0.007	0.008	0.036	0.038	0.557	0.223
	2002-2018	$\beta^{(j)}$	-1.781	0.038	-0.545	0.458	0.460	0.061
		t-Stat	[-1.826]	[0.029]	[-0.630]	[1.114]	[3.013]	[0.256]
		R^2	0.021	0.000	0.007	0.048	0.332	0.030
CO2-PET	1986-2002	$\beta^{(j)}$	-0.441	-1.535	1.017	0.533	0.446	0.782
		t-Stat	[-1.571]	[-1.926]	[4.312]	[1.909]	[3.156]	[4.784]
		R^2	0.003	0.068	0.136	0.154	0.376	0.617
	2002-2018	$\beta^{(j)}$	1.170	0.862	-0.420	0.152	0.420	0.426
		t-Stat	[2.444]	[2.920]	[-1.333]	[0.868]	[3.132]	[3.133]
		R^2	0.038	0.031	0.037	0.029	0.496	0.738
CO2-TOT	1986-2002	$\beta^{(j)}$	-0.287	-0.497	0.942	0.650	0.704	0.628
		t-Stat	[-0.645]	[-0.664]	[5.718]	[3.315]	[11.334]	[3.533]
		R^2	0.002	0.008	0.154	0.309	0.805	0.863
	2002-2018	$\beta^{(j)}$	-0.364	0.428	-0.165	0.675	0.610	0.296
		t-Stat	[-0.985]	[0.753]	[-0.351]	[2.889]	[3.314]	[3.639]
		R^2	0.004	0.004	0.003	0.323	0.662	0.876

Notes: This table presents the Ordinary Least Squares (OLS) estimate of the slope coefficient from Equation (5) over different subsamples for each timescale, along with corresponding t-statistic and coefficient of determination (R^2). The t-statistics are calculated using Newey-West HAC robust standard errors with a lag length truncation of $2^j - 1$.

at larger timescales (and not small scales) is unaffected by splitting up the sample.

5.3 Choice of Wavelet Filter

In all of the preceding analysis, we have derived the MRA for all series using the MODWT based on the Haar wavelet filter, which is the simplest of a large number of families of wavelet filters. In this section we will check the sensitivity of our results by changing the wavelet filter to one with a larger width, namely the so-called $D(4)$ filter; the fourth member of the class of discrete Daubechies wavelets (see Percival and Walden, 2000, for a complete description of these wavelet filters).

Figures 7 and 8 in the Appendix show the graphs of the MRA components $e_t^{(j)}$ and $\widehat{\mathbf{f}}_t^{(j)}$ from using the $D(4)$ wavelet filter along with the associated autocorrelation plots, in a similar way to Figures 3 and 4, above, for the Haar filter. From a graphical inspection it can be seen that the results are virtually identical to that of the Haar filter, but that there is a higher degree of smoothness from the $D(4)$ filter. This is particularly noticeable in the $j = 6$ case for total energy CO_2 emissions.

Table 6: Regression Results by Timescale - Daubechies $D(4)$ Wavelet Filter

		Scale (j)					
		1	2	3	4	5	6
CO2-COAL	$\beta^{(j)}$	0.309	0.378	0.423	1.218	1.014	0.663
	t-Stat	[0.534]	[0.653]	[0.935]	[2.984]	[2.784]	[0.582]
	R^2	0.001	0.002	0.007	0.190	0.312	0.378
CO2-GAS	$\beta^{(j)}$	-1.179	0.938	0.281	0.414	0.658	0.202
	t-Stat	[-0.943]	[1.157]	[0.399]	[0.857]	[1.526]	[0.537]
	R^2	0.009	0.006	0.002	0.020	0.340	0.195
CO2-PET	$\beta^{(j)}$	0.106	-0.676	0.526	0.300	0.404	0.430
	t-Stat	[0.221]	[-1.875]	[1.401]	[0.879]	[2.267]	[1.969]
	R^2	0.000	0.016	0.040	0.064	0.372	0.449
CO2-TOT	$\beta^{(j)}$	-0.152	0.035	0.395	0.626	0.644	0.442
	t-Stat	[-0.314]	[0.082]	[0.925]	[2.518]	[3.628]	[0.628]
	R^2	0.001	0.000	0.014	0.198	0.522	0.735

Notes: This table presents the Ordinary Least Squares (OLS) estimate of the slope coefficient from Equation (5) for each timescale, along with corresponding t-statistic and coefficient of determination (R^2). The wavelet filter has been changed to that of the $D(4)$ filter. The t-statistics are calculated using Newey-West HAC robust standard errors with a lag length truncation of $2^j - 1$.

Table 6 confirms that the results are very insensitive to the choice of the wavelet filter, with little qualitative change in the estimates of the regression in Equation (5) relative to those using the Haar filter. The sign and significance of the coefficients are very similar to those in Table 3. The R^2 has risen in many of the regressions which is probably due to the slightly higher smoothness and therefore persistence of the series. We also ran results using the $D(8)$ filter which were very similar and therefore not repeated here.

6 Conclusion

This paper has moved the debate away from the long-run relationship between economic activity and emissions which has become saturated in the EKC literature. Instead, we look at this problem from a short-to-medium run perspective. We propose a novel econometric methodology which allows us to look at emissions and the economy over different cycle frequencies. This method also allows the number of economic proxies to be large by using a “big data” factor model technique, where the principal component is taken from all series before being decomposed to different timescales. Our approach reduces the reliance of the existing empirical literature on the specific choice of economic proxies.

In the results of the paper we firstly analyse the patterns found in the constructed series for economic activity and emissions at different timescales. We notice that the economic activity variable has high correlation with existing indices of U.S. economic activity such as the FRED Leading Index. Given that our decomposition of the economic variables are strongly linked to the business cycle, we are therefore confident that the equivalent decompositions for CO_2 emissions are a good measure of emissions cycles.

The main results focus on the link between emissions and the economy at different cycle frequencies. The key conclusion we draw is that, when looking at movements in CO_2 emissions and economic activity at a frequency of one-month changes, it appears that there is no significant relationship as both series tend to be noisy at this frequency. However, when applying the timescale decomposition at lower frequencies of around one to three years, the cycles in both emissions and economic activity *are* indeed significantly interlinked. The consequence of this result is that the linkage between the environment and economic activity may be masked by not using an appropriate filter. This means that short-to-medium run environmental damages still arise from increases in economic activity and should not be ignored by policymakers and the public. Since we find a meaningful relationship at timescales shorter than electoral cycles, it seems that politicians should plan their economic policy not just in the context of their financial implications, but also in terms of environmental impact.

7 Appendix

Figure 5: CO_2 Emissions by Source from 1978-2018

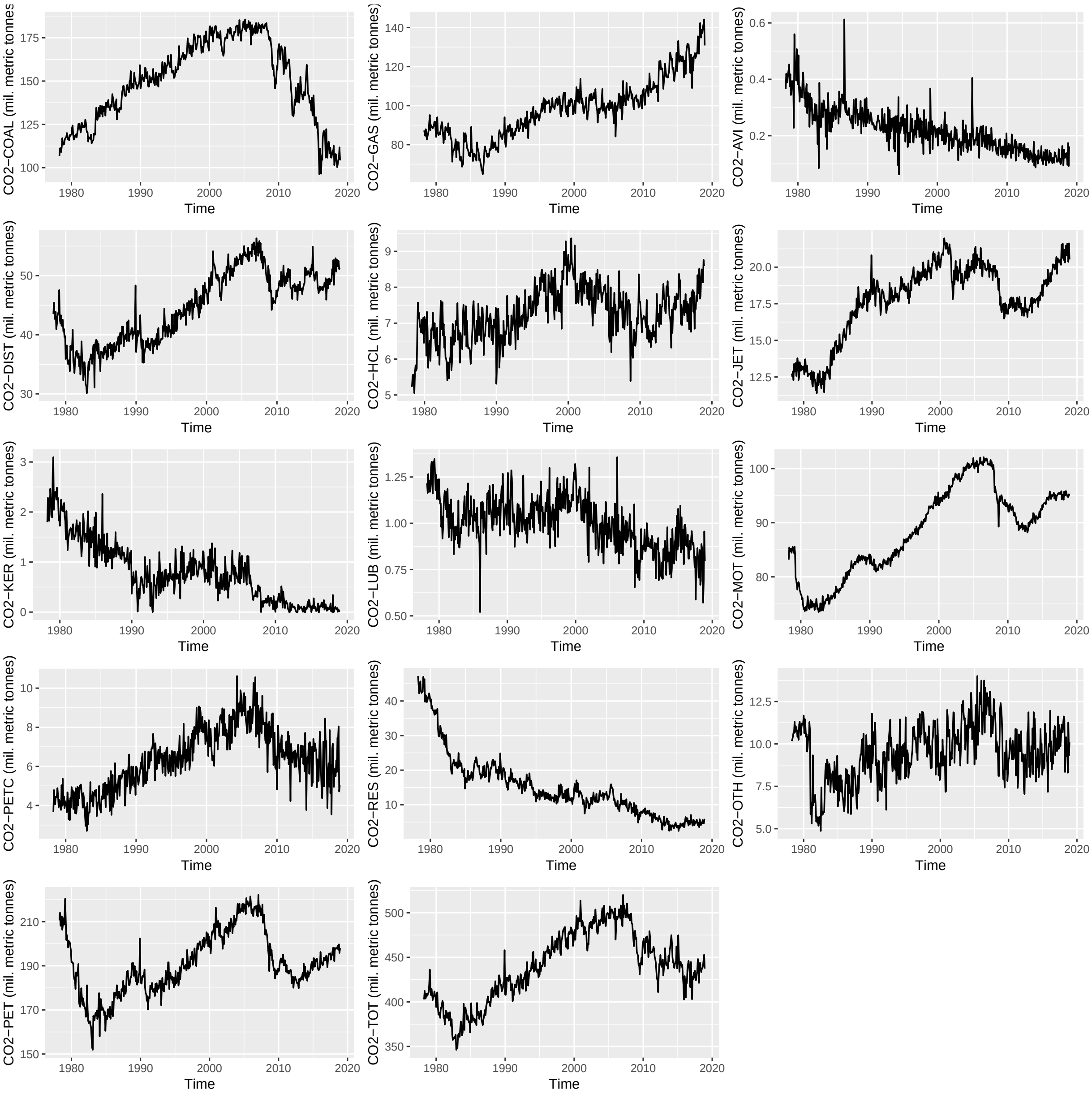


Figure 6: CO_2 Emission Composition over Time

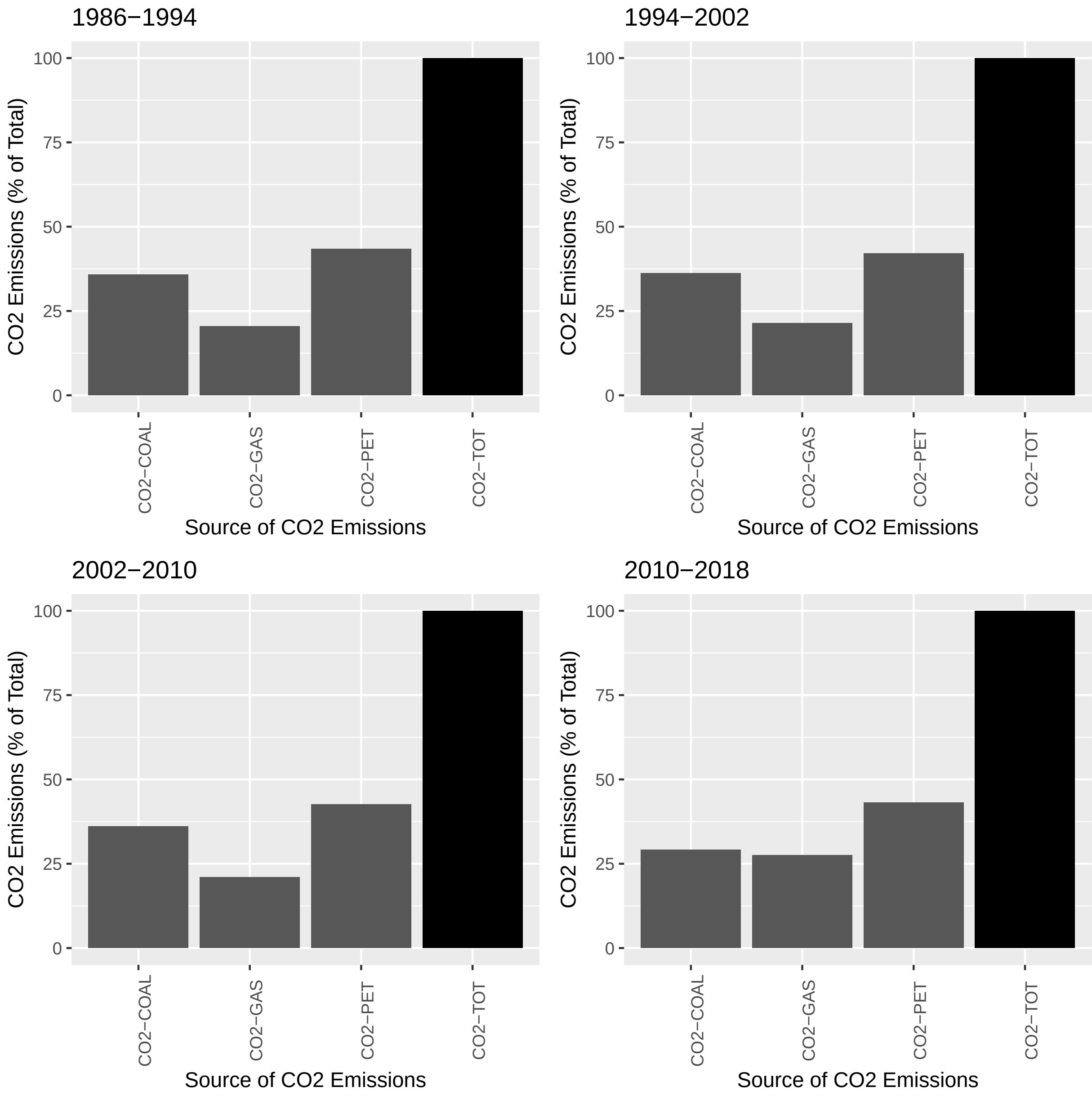
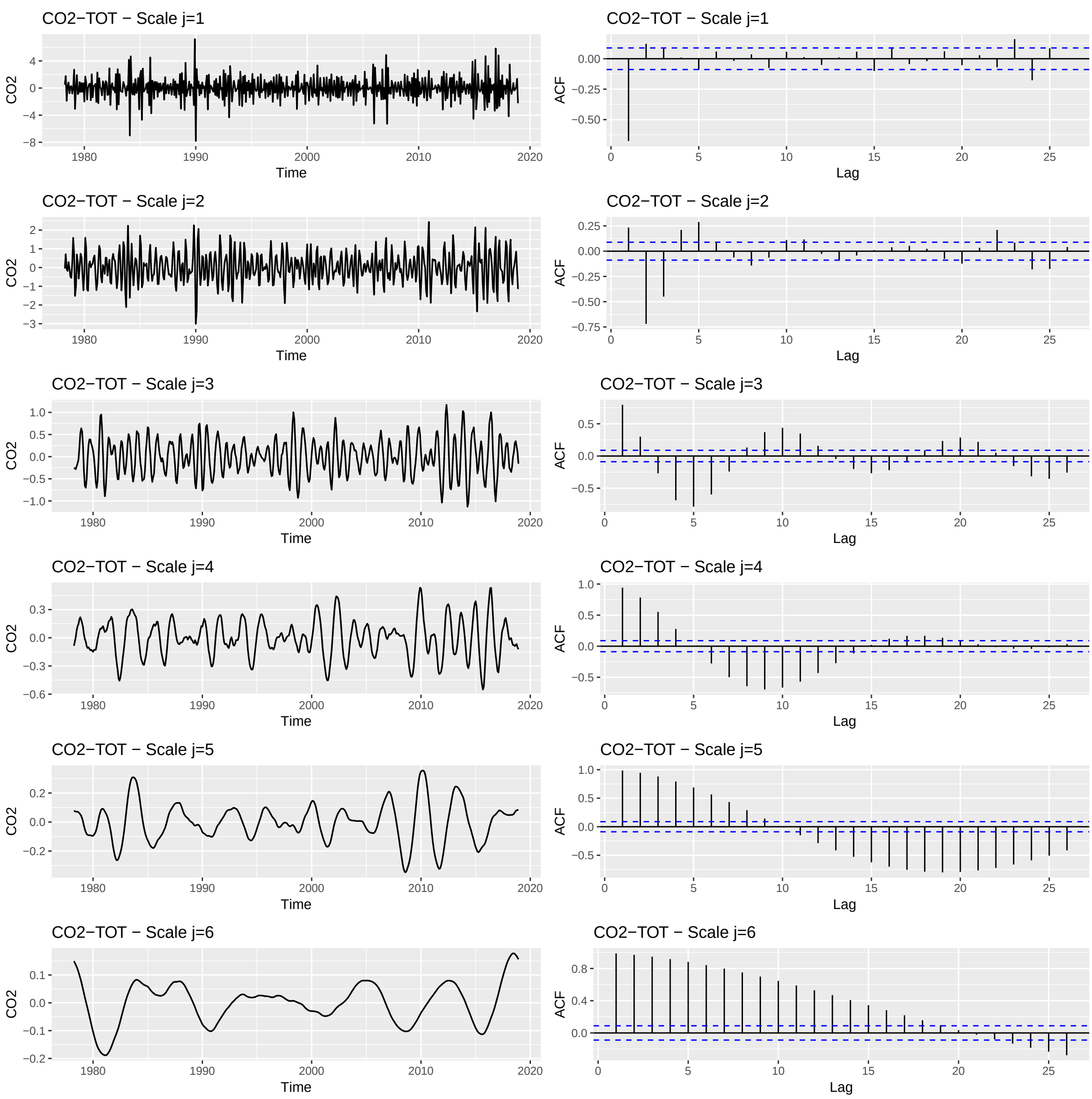
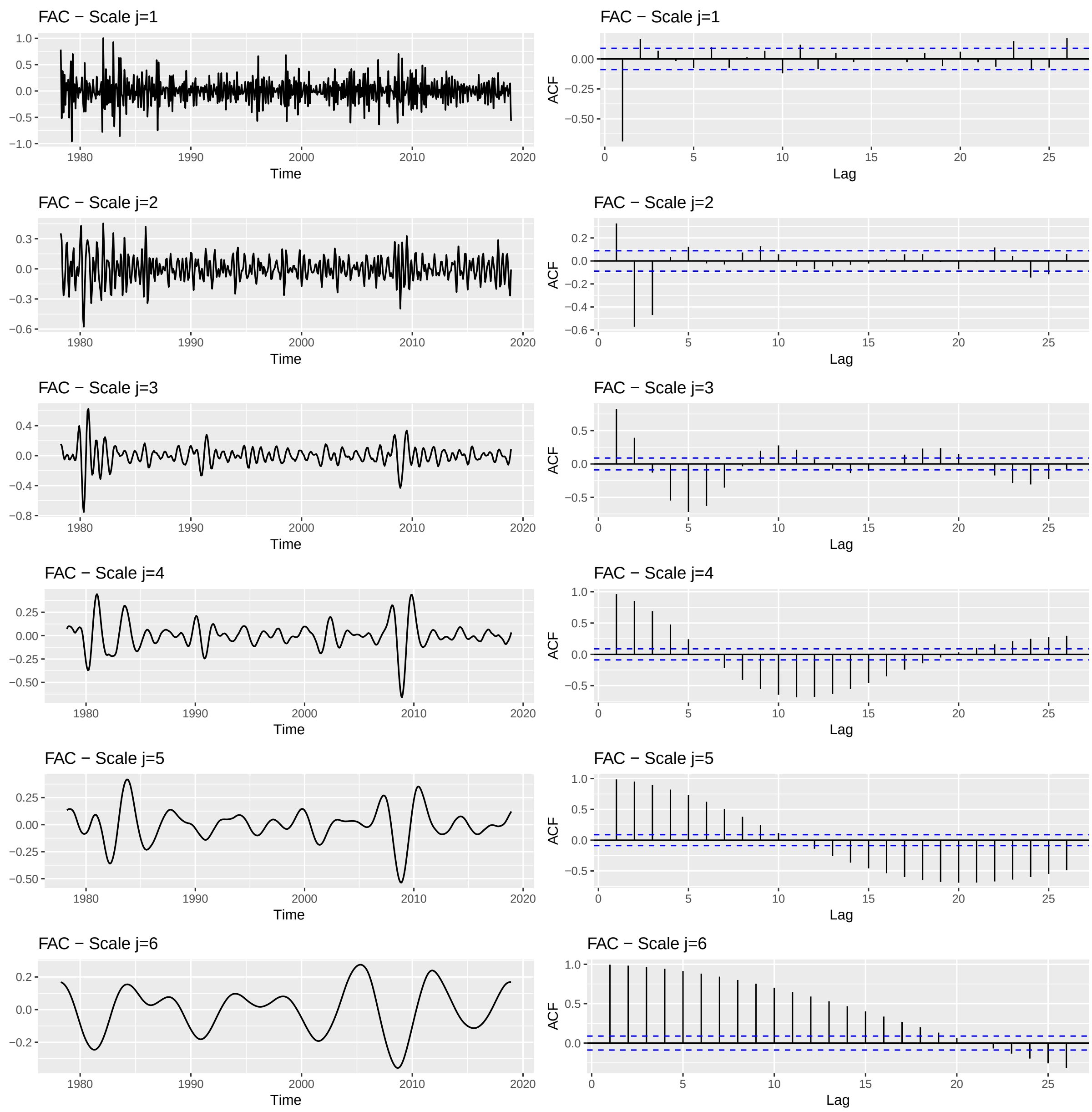


Figure 7: MRA for Total Energy CO_2 Emissions, $D(4)$ Wavelet Filter



Notes: The MRA is based on the MODWT using the Daubechies $D(4)$ wavelet filter.

Figure 8: MRA for the Single Factor, $D(4)$ Wavelet Filter



Notes: The MRA is based on the MODWT using the Daubechies $D(4)$ wavelet filter.

References

Al-Mulali, U., B. Saboori, and I. Ozturk (2015). Investigating the Environmental Kuznets Curve Hypothesis in Vietnam. *Energy Policy 76*, 123–131.

Antolin Diaz, J., T. Drechsel, and I. Petrella (2017). Tracking the Slowdown in Long-Run GDP Growth. *Review of Economics and Statistics 99*(2), 343–356.

Auffhammer, M. and R. Steinhauser (2012). Forecasting the path of US CO2 emissions using state-level information. *Review of Economics and Statistics 94*(1), 172–185.

Bai, J. (2003). Inferential theory for factor models of large dimensions. *Econometrica 71*(1), 135–171.

Bai, J. and S. Ng (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica 70*(1), 191–221.

Bai, J. and S. Ng (2006). Confidence Intervals for Diffusion Index Forecasts and Inference for Factor-Augmented Regressions. *Econometrica 74*(4), 1133–1150.

Bai, J. and S. Ng (2008). Forecasting Economic Time Series Using Targeted Predictors. *Journal of Econometrics 146*(2), 304–317.

Bai, J. and S. Ng (2009). Boosting Diffusion Indices. *Journal of Applied Econometrics 24*(4), 607–629.

Balaguer, J. and M. Cantavella (2016). Estimating the environmental Kuznets curve for Spain by considering fuel oil prices (18742011). *Ecological Indicators 60*, 853–859.

Banbura, M., D. Giannone, M. Modugno, and L. Reichlin (2013). Now-Casting and the Real-Time Data Flow. In G. Elliott and A. Timmermann (Eds.), *Handbook of Economic Forecasting*, Volume 2A, pp. 195–236. Amsterdam: North-Holland.

Bańbura, M. and M. Modugno (2014). Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data. *Journal of Applied Econometrics 29*(1), 133–160.

Bandi, F. M., B. Perron, A. Tamoni, and C. Tebaldi (2019). The Scale of Predictability. *Journal of Econometrics 208*(1), 120–140.

Breitung, J. and S. Eickmeier (2011). Testing for Structural Breaks in Dynamic Factor Models. *Journal of Econometrics 163*(1), 71–84.

Burnett, J. W., J. C. Bergstrom, and M. E. Wetzstein (2013). Carbon dioxide emissions and economic growth in the US. *Journal of Policy Modeling 35*(6), 1014–1028.

[dataset] Federal Reserve Bank of St. Louis (2019). Federal Reserve Economic Data (FRED). URL: https://fred.stlouisfed.org/.

[dataset] U.S. Energy Information Administration (2019). Monthly Energy Review. URL: https://www.eia.gov/totalenergy/data/monthly/.

Dong, J., D. Davidson, F. Southworth, and T. Reuscher (2012). Analysis of Automobile Travel Demand Elasticities With Respect To Travel Cost. *Federal Highway Administration Report*.

Fosten, J. and D. Gutknecht (2019). Testing Nowcast Monotonicity with Estimated Factors. *Journal of Business & Economic Statistics (forthcoming)*.

Gencay, R. and D. Signori (2015). Multi-scale Tests for Serial Correlation. *Journal of Econometrics 184*(1), 62–80.

Grossman, G. M. and A. B. Krueger (1995). Economic Growth and the Environment. *The Quarterly Journal of Economics 110*(2), 353–377.

Halicioglu, F. (2009). An econometric study of CO2 emissions, energy consumption, income and foreign trade in Turkey. *Energy Policy 37*(3), 1156–1164.

Holtz-Eakin, D. and T. M. Selden (1995). Stoking the fires? CO2 emissions and economic growth. *Journal of Public Economics 57*(1), 85–101.

Hood, E. M., L. Merlivat, and T. Johannessen (1999). Variations of fCO2 and air-sea flux of CO2 in the Greenland Sea gyre using high-frequency time series data from CARIOCA drift buoys. *Journal of Geophysical Research: Oceans 104*(C9), 20571–20583.

Jebli, M. B., S. B. Youssef, and I. Ozturk (2016). Testing environmental Kuznets curve hypothesis: The role of renewable and non-renewable energy consumption and trade in OECD countries. *Ecological Indicators 60*, 824–831.

Kang, B. U., F. In, and T. S. Kim (2017). Timescale betas and the cross section of equity returns: Framework, application, and implications for interpreting the Fama–French factors. *Journal of Empirical Finance 42*, 15–39.

Lau, L.-S., C.-K. Choong, and Y.-K. Eng (2014). Investigation of the environmental Kuznets curve for carbon emissions in Malaysia: Do foreign direct investment and trade matter? *Energy Policy 68*, 490–497.

Ludvigson, S. C. and S. Ng (2007). The Empirical Risk-Return Relation: A Factor Analysis Approach. *Journal of Financial Economics 83*(1), 171–222.

McCracken, M. and S. Ng (2016). FRED-MD: A Monthly Database for Macroeconomic Research. *Journal of Business & Economic Statistics Economic Statisics 34*(4), 574–589.

Newey, W. K. and K. D. West (1987). A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica 55*(3), 703–708.

Ortu, F., A. Tamoni, and C. Tebaldi (2013). Long-run risk and the persistence of consumption shocks. *Review of Financial Studies 26*(11), 2876–2915.

Pablo-Romero, M., L. Cruz, and E. Barata (2017). Testing the transport energy-environmental Kuznets curve hypothesis in the EU27 countries. *Energy Economics 62*, 257–269.

Percival, D. B. and A. T. Walden (2000). *Wavelet Methods for Time Series Analysis.* Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press.

Rua, A. (2011). A wavelet approach for factor-augmented forecasting. *Journal of Forecasting 30*(7), 666–678.

Selden, T. M. and D. Song (1994). Environmental quality and development: is there a Kuznets curve for air pollution emissions? *Journal of Environmental Economics and Management 27*(2), 147–162.

Soytas, U. and R. Sari (2009). Energy Consumption, Economic Growth, and Carbon Emissions: Challenges Faced by an EU Candidate Member. *Ecological Economics 68*(6), 1667–1675.

Soytas, U., R. Sari, and B. T. Ewing (2007). Energy Consumption, Income, and Carbon Emissions in the United States. *Ecological Economics 62*(3), 482–489.

Stock, J. H. and M. W. Watson (2002a). Forecasting Using Principal Components from a Large Number of Predictors. *Journal of the American Statistical Association 97*(460), 1167–1179.

Stock, J. H. and M. W. Watson (2002b). Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business and Economic Statistics 20*(2), 147–162.

Stock, J. H. and M. W. Watson (2009). Forecasting in Dynamic Factor Models Subject to Structural Instablility. In J. Castle and N. Shephard (Eds.), *The Methodology and Practice of Econometrics: a Festschrift in Honour of David F. Hendry*, pp. 173–205. Oxford: Oxford University Press.

Stock, J. H. and M. W. Watson (2016). Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. In J. B. Taylor and H. Uhlig (Eds.), *Handbook of Macroeconomics*, Volume 2, pp. 415–525. Elsevier.

Xyngis, G. (2017). Business-cycle variation in macroeconomic uncertainty and the cross-section of expected returns: Evidence for scale-dependent risks. *Journal of Empirical Finance 44*, 43–65.

Zivot, E. and D. W. K. Andrews (1992). Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *Journal of Business & Economic Statistics 10*(3).